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# An Empirical Evaluation of Denoising Techniques for Streaming Data

J. L. Thompson

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# An Empirical Evaluation of Denoising Techniques for Streaming Data

Jeremy Luke Thompson\*

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## Abstract

We investigate denoising techniques for streaming data. This is data that is analyzed while it is collected. We consider spatial filters, such as the box filter, Gaussian smoothing, and the bilateral filter; frequency-based techniques, such as fast Fourier transform and wavelet transform, combined with thresholding of the coefficients; and a statistical neighborhood filter, the non-local means algorithm. We discuss practical concerns for incremental implementation, such as edge treatment, incremental updating, and parameter stability. These methods are applied to both synthetic data and real world data. Based on several carefully designed experiments, we note situations when these methods could fail and make recommendations for their use with real world data. Specifically, we suggest the use of the bilateral filter alone or a combination of the bilateral filter and non-local means algorithm.

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\*United States Air Force Academy and Lawrence Livermore National Laboratory

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# 1 Introduction

A time series is any temporally ordered series of observations. Frequently, as when collecting observations of various real world phenomenon, these observations will be contaminated with a variety of errors, or noise, such as sampling and processing errors. In traditional time series data, the denoising is done after the data has been collected. As a result, there is an opportunity to try different denoising techniques and experiment with different parameters to select a method that works best for a data set. Our focus in this report is on streaming data, where the data is analyzed as it is collected. We therefore consider techniques that can be applied incrementally. We discuss multiple classes of techniques and practical considerations for incremental implementation such as edge treatment and incremental updating. We investigate how we can select the parameters for the algorithms so that the same parameters can be used over time, while yielding acceptable results. Additionally, we assess the performance of these techniques in the context of peak signal to noise ratio for known time series with added noise and optimal parameter stability.

Many denoising techniques rely upon an estimate of the variance of the distribution this random noise comes from, typically assumed to be Gaussian. Gasser, et al. [7] describe a method for estimating this unknown value based upon the sum of squared differences between the observed data and linear interpolations approximating the true values of the time series. In this report, we use the notation  $y_i$  for the values of the time series at time index  $i$ . For a time series with  $N$  values, starting at  $i = 0$ , the estimated noise variance as given in [7] is:

$$\hat{\sigma}_n^2 = \frac{2}{3(N-2)} \sum_{i=1}^{N-2} \left( \frac{1}{2}y_{i-1} - y_i + \frac{1}{2}y_{i+1} \right)^2$$

As discussed later in the report, we use this estimate to set the parameters of some of the denoising techniques we investigate. There are, naturally, a variety of other techniques [4, 10] for noise variance estimation, with different levels of robustness and computational difficulty. We use Equation 1 because of its simplicity.

The report is organized as follows. A description of the denoising techniques we will use is given in Section 2. We discuss the design of experiment for empirical comparison of these denoising methods in Section 3. Experimental results on both synthetic and real world data are discussed in Section 4 and 5. We conclude our evaluation and provide recommendations along with suggestions for future work in Section 6.

## 2 Denoising techniques

There are a variety of denoising techniques, and they fit into three broad categories: local smoothing filters, frequency coefficient thresholding techniques, and statistical neighborhood filters. We discuss three spatial filters: the box filter, Gaussian filter, and bilateral filter; two frequency techniques: Fourier transform and wavelet transform, with coefficient thresholding; and one statistical neighborhood filter, the non-local means algorithm. Besides these common methods, we propose combination approaches derived from them.

The color convention for charts in this report is black for the true time series values, if known, blue for the noisy time series values, red for the denoised time series values, and cyan for the residuals, the difference between the noisy and denoised time series values.

## 2.1 Spatial filters

### 2.1.1 Box filter

The box filter is the simplest denoising technique and is a uniformly weighted moving average of the time series. This technique works best in time series with true values that do not change rapidly so the noise averages to zero over an interval while the true time series values remain relatively unchanged. Smoothed values are given by

$$s_i = \sum_{j \in I} w(i, j) y_j,$$

where the weights are given by the function

$$w(i, j) = \frac{1}{|I|},$$

and  $|I|$  is the size of the time interval, or window, of the filter. Typically the interval is symmetric about the point of interest, which means  $|I|$  is odd. In this technique, the interval size is a parameter to be chosen by the analyst. Figure 1 shows the weighting scheme for the box filter.

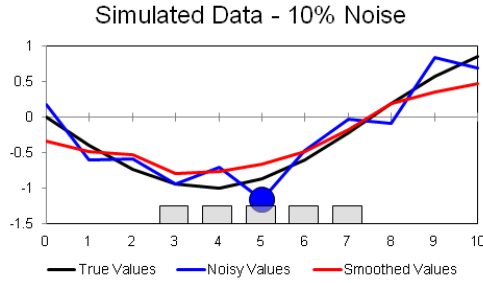


Figure 1: Box Filter Weighting Scheme

In time series where intensity values change rapidly, this technique removes features of interest in the time series. Figure 2 shows the performance of the box filter on simulated data generated from the composition of two sine functions and a sawtooth function. The box filter does a reasonable job removing noise, but it destroys features in the time series, such as the three jumps at the end of these sawteeth. The damage to the three jumps can be seen in the residuals, shown in cyan in the figure. This damage is one of the reasons the box filter is not used in practice.

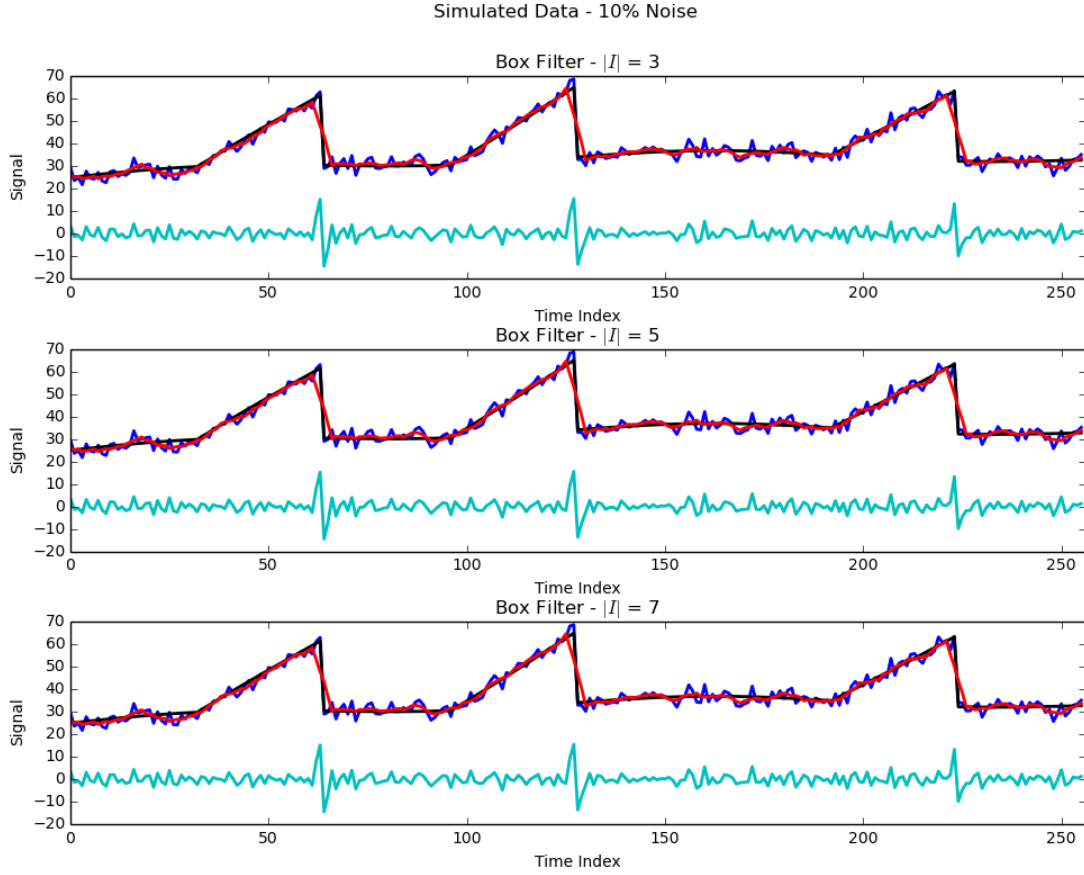


Figure 2: Box Filter With Simulated Data

### 2.1.2 Gaussian filter

The Gaussian filter is a weighted moving average that weights points based upon their distance from the point of interest according to a Gaussian distribution with standard deviation  $\sigma_d$ . The smoothed values from the Gaussian filter are given by

$$s_i = \sum_{j \in I} w(i, j) y_j$$

where the weights are given by the function

$$w(i, j) = \frac{1}{z_i} e^{-\frac{|i-j|}{2\sigma_d^2}}$$

and  $z_i$  is a normalization factor so the weights sum to 1 on the interval.

Typically a interval width of  $10\sigma_d$  is used. This accounts for 99.99994% of the Gaussian distribution. Some computations can be saved by using an interval width of  $8\sigma_d$ , 99.994% of the Gaussian distribution, or  $6\sigma_d$ , 99.7% of the Gaussian distribution. In this technique, the Gaussian kernel standard deviation,  $\sigma_d$ , is a parameter to be chosen by the analyst. Figure 3 shows the weighting scheme for the Gaussian filter.

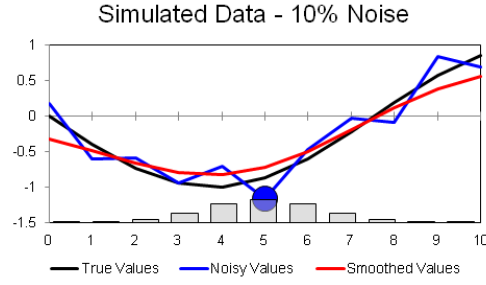


Figure 3: Gaussian Filter Weighting Scheme

As seen in Figure 4, the Gaussian filter does a reasonable job removing noise but also destroys features in the time series, albeit to a lesser degree than for a box filter with the same window size. The damage to the three jumps can again be seen in the residuals, shown in cyan in the figure.

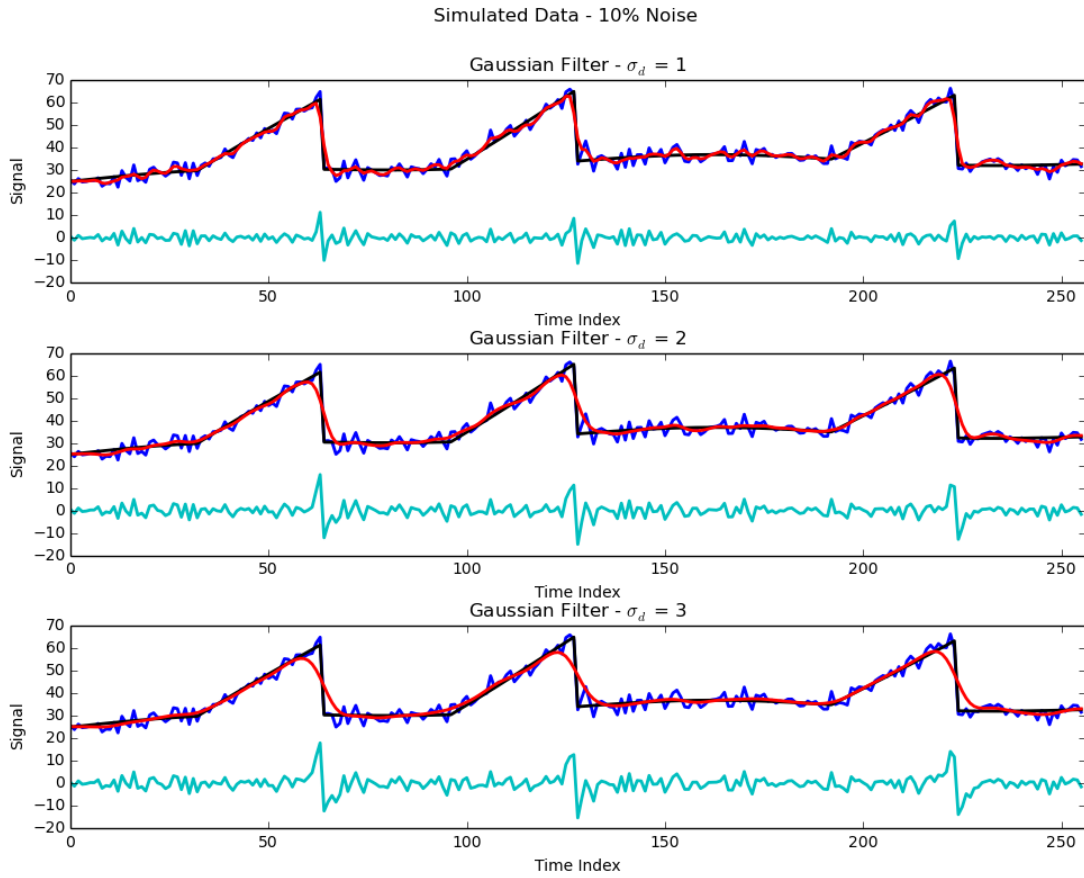


Figure 4: Gaussian Filter with Simulated Data



### 2.1.3 Bilateral filter

The bilateral filter [13] attempts to better preserve features in the time series by applying a pair of Gaussian weights, one for spatial distance, as in the Gaussian filter, and one for differences in intensity values. The smoothed values from the bilateral filter are given by

$$s_i = \sum_{j \in I} w(i, j) y_j$$

where the weights are given by the function

$$w(i, j) = \frac{1}{z_i} e^{-\frac{|i-j|}{2\sigma_d^2}} e^{-\frac{|y_i - y_j|}{2\sigma_i^2}}$$

and, as before,  $z_i$  is a normalization factor.

As with the Gaussian filter, an interval width of  $10\sigma$  is typical. In this technique, the Gaussian kernel standard deviations,  $\sigma_d$  and  $\sigma_i$ , are two parameters to be chosen by the analyst. Figure 5 shows the weighting scheme for the bilateral filter.

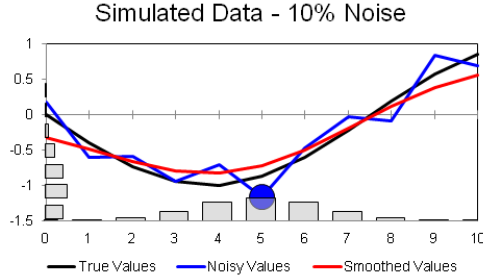


Figure 5: Bilateral Filter Weighting Scheme

As seen in Figure 6, the bilateral filter does a reasonable job both smoothing the time series and retaining features. Damage to the three jumps cannot be seen in the residuals. Unfortunately, the bilateral filter may retain some of the noise, particularly if the noise causes a significant change in intensity value.

Zang and Gunturk [16] suggest that the optimal value of the standard deviation of the spatial Gaussian kernel,  $\sigma_d$ , is in the range  $[1.5, 2.1]$  and the standard deviation of the intensity Gaussian kernel,  $\sigma_i$ , is in the range  $[1.5\hat{\sigma}_n, 3\hat{\sigma}_n]$  for 2D image processing. Recall that  $\hat{\sigma}_n$  is the noise standard deviation estimate. It is uncertain if these results translate to 1D time series denoising.

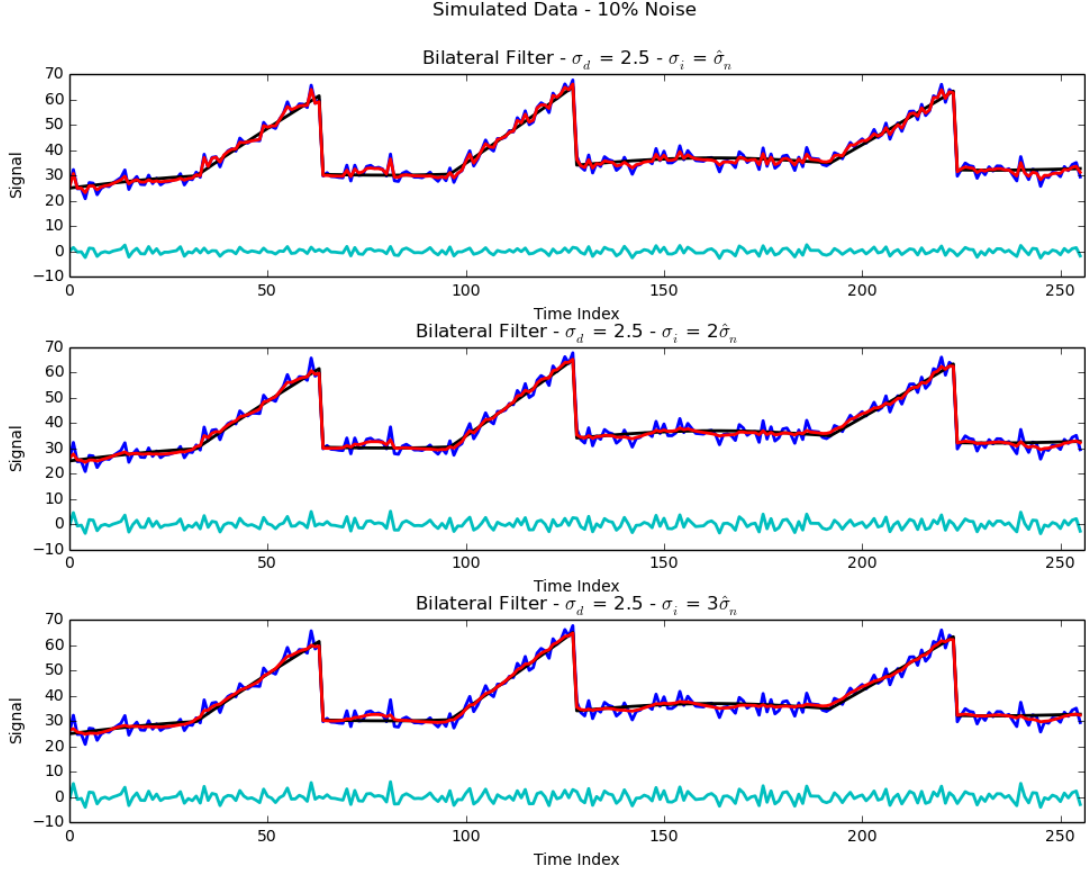


Figure 6: Bilateral Filter with Simulated Data

#### 2.1.4 Treatment of edge values in spatial filters

It is important to note that treatment of edge values is particularly important when incrementally processing a time series as the most relevant data is in the leading edge of the data set. In the case of spatial filters, the  $\frac{|I|-1}{2}$  values on each edge do not have complete intervals. We adjust normalization factor  $z_i$  to ensure that the weight values in the incomplete interval still sum to 1. Figure 7 shows the adjusted weighting scheme for the box filter for the most recent data point, highlighted in blue.

With this edge treatment, it is simple to adjust the time series when a new data point is received. With the updated time series, the last  $\frac{|I|-1}{2}$  smoothed values can be updated and a new smoothed value can be calculated as before. Figure 7 also highlights the updated values, in red. These comments on edge treatment and incrementing also apply to our implementation of the other spatial filters, namely the Gaussian and bilateral filters.

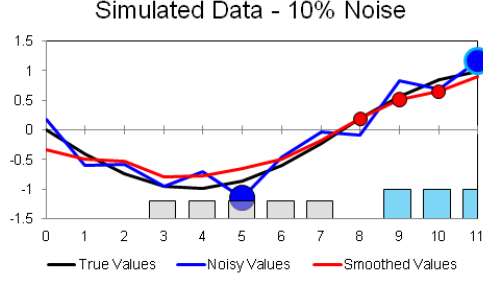


Figure 7: Updated Edge Values for Local Smoothing Filters

## 2.2 Frequency techniques

### 2.2.1 Fourier transform

Historically, analysis in the frequency domain was conducted via the Fourier transform in its rapid discrete form, the Fast Fourier Transform (FFT). The FFT takes uniformly spaced observations and can transform the data relatively quickly. After transformation, coefficient thresholding is used on the time series frequency coefficients to denoise the data, and then the denoised frequency coefficients are reverse transformed.

There are two common procedures for modifying noisy frequency coefficients, known as thresholding methods [4]. The first, hard thresholding, cancels all coefficients smaller than a particular threshold.  $v(\alpha)$  represents the frequency coefficients of the time series, the result of transforming data. In hard thresholding, the denoised coefficients are given by:

$$v(\alpha) = \begin{cases} v(\alpha) & |v(\alpha)| > \mu \\ 0 & |v(\alpha)| < \mu \end{cases}$$

Hard thresholding can create outliers, which can be partially avoided using soft thresholding. In soft thresholding the denoised coefficients are given by:

$$v(\alpha) = \begin{cases} v(\alpha) - \text{sgn}(v(\alpha)) \mu & |v(\alpha)| \geq \mu \\ 0 & |v(\alpha)| < \mu \end{cases}$$

Unfortunately, soft thresholding can create problems with the scale of the reverse transformed data which can make it inappropriate for time series where the scale of the data is important. For this reason, we will only consider hard thresholding. In this algorithm, the analyst can control the choice of hard or soft thresholding and the thresholding cutoff,  $\mu$ .

The theoretically optimal threshold is  $\mu = \sigma\sqrt{2\log I}$ , where  $I$  is the number of data points and  $\sigma$  is the standard deviation of the coefficients. In order to avoid inflating the standard deviation of the coefficients through a large coefficient corresponding to the mean of the data, the mean is subtracted from the time series prior to transformation, making the time series a zero-mean dataset. In practice this threshold is too high and cancels too many coefficients that do not correspond to noise. Instead,  $\mu = 3\sigma$  is used for hard thresholding and  $\mu = \frac{3}{2}\sigma$  is used for soft thresholding [1] for 2D image processing. It is uncertain if these results translate to 1D time series denoising.

As can be seen in Figure 8, the Fourier transform struggles near the edges, where Gibbs phenomenon may occur. This makes the Fourier transform less than ideal for incremental data denoising, where the most relevant data is near the end of the time series.

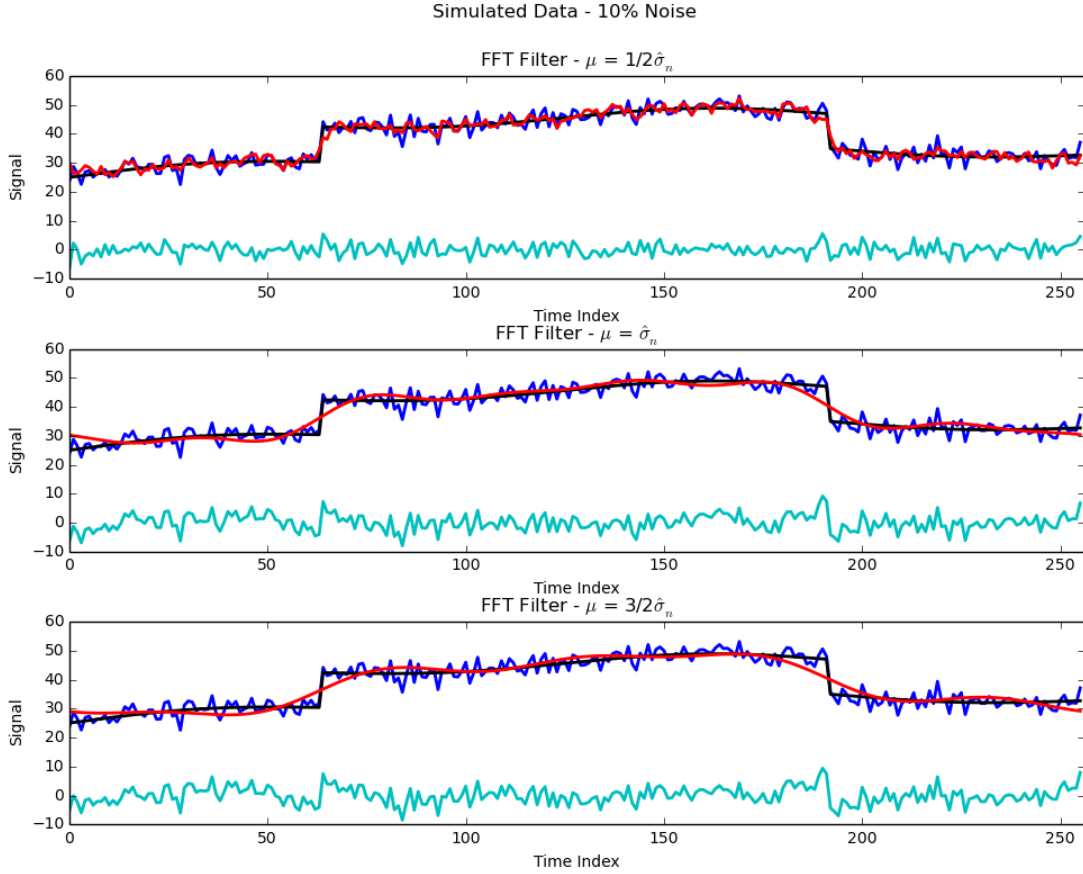


Figure 8: Fourier Transform Filter with Simulated Data

Incremental updates present a problem for the Fourier transform, as the transform can only be applied to multiple data points, and larger data sets are better. This means that it takes more computations to incrementally update Fourier transform coefficient thresholding smoothed time series than locally smoothed time series.

### 2.2.2 Wavelet transform

The wavelet transform is one of the most popular frequency domain alternatives to the Fourier transform. While the Fourier transform completely transforms the time series into the frequency domain, the wavelet transform offers both frequency and time information by fitting a series of finite length functions, wavelets, to the time series. One such wavelet is the Haar wavelet, Figure 9. This allows for filtering both by frequency and temporal relationships [8]. There are a variety of wavelet families to choose from, and the wavelet transformations can be repeated to a desired level of resolution. We use the Haar wavelet due to its simplicity, but many other families of wavelets give better performance.

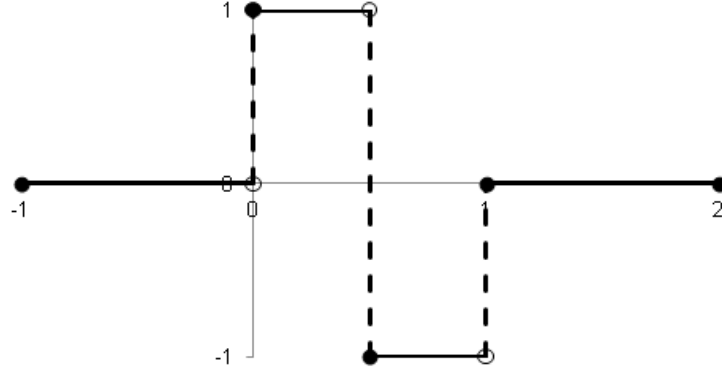


Figure 9: Haar Wavelet

Mota, Vasconcelos, and Silva [11] outlined an algorithm for processing continuous data streams in real time using the discrete wavelet transform, inspired by an older result by Vishwanath, called the Recursive Pyramid Algorithm [15].

Once the data has been wavelet transformed, the data is denoised via frequency coefficient thresholding, as with the Fourier transform [6].

In this technique, the analyst chooses the wavelet family, the number of levels of decomposition, and the thresholding cutoff,  $\mu$ . Figure 10 shows the results from denoising with a Haar wavelet transform, with different hard thresholds.

In this case, there is no special edge treatment. Incremental data processing is often accomplished via a real time algorithm, as mentioned above and frequency coefficients are thresholded and back transformed immediately afterwards.

## 2.3 Statistical neighborhood filters

### 2.3.1 The non-local means algorithm

Statistical neighborhood filters attempt to fix the problems associated with local smoothing filters by calculating the smoothed value as a weighted average of other values in the time series based upon the similarity between the neighborhoods around the time series values. Figure 11 shows three neighborhoods highlighted in the time series. The values in the green window are more similar to the values in the black window than the values in the red window and, thus, should be weighted higher.

The non-local means algorithm was first introduced by Buades et al. [1]. Non-local means has primarily been used for image processing, but it has been mentioned in a 1D context in several papers ([2], [14], [17]). We use a modification of this algorithm for efficient 3D medical image processing by Coupé et al. [3].

In the non-local means algorithm, smoothed values are given by

$$s_i = \sum_{j \in N} w(i, j) y_j$$

where the weights are given by the function

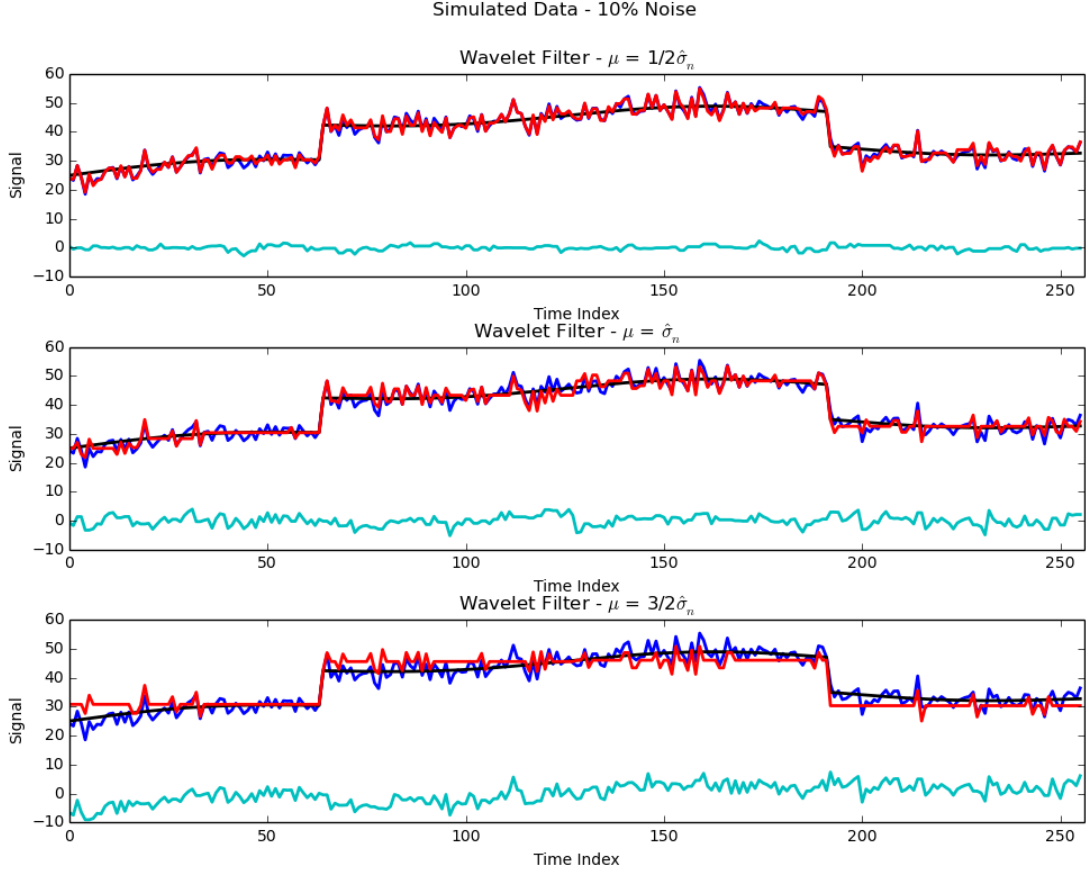


Figure 10: Wavelet Transform Filter with Simulated Data

$$w(i, j) = \frac{1}{z_i} e^{-\frac{|Y_i - Y_j|^2}{2\beta\hat{\sigma}_n^2|Y|}}$$

In this scheme,  $Y_i$  is a vector of intensity values in the window, or neighborhood, around  $y_i$ ,  $|Y_i - Y_j|$  is the  $L_2$  norm of the difference in intensity values in these intervals,  $|Y|$  is the window size, and  $\beta$  is a parameter chosen by the analyst to control the amount of smoothing. According to Coupé et al. [3],  $\beta$  varies between 0.0 and 1.0, with values of  $\beta$  closer to 1.0 better for high levels of noise and values of  $\beta$  closer to 0.5 better for lower levels of noise.

Duval et al. [5] notes that neighborhood preselection can improve the results of the non-local means algorithm by assigning a weight of 0 to the  $y_j$  values that have neighborhoods that are too dissimilar to the neighborhood,  $Y_i$ , under consideration. Duval et al. uses a preselection test based upon the norm of the difference between neighborhoods. A more complex preselection method is described by Buades et al. [1]. We use Duval et al.'s preselection test:

$$w(i, j) = \begin{cases} \frac{1}{z_i} e^{-\frac{|Y_i - Y_j|^2}{2\beta\hat{\sigma}_n^2|Y|}} & |Y_i - Y_j| < T \\ 0 & \text{otherwise} \end{cases}$$

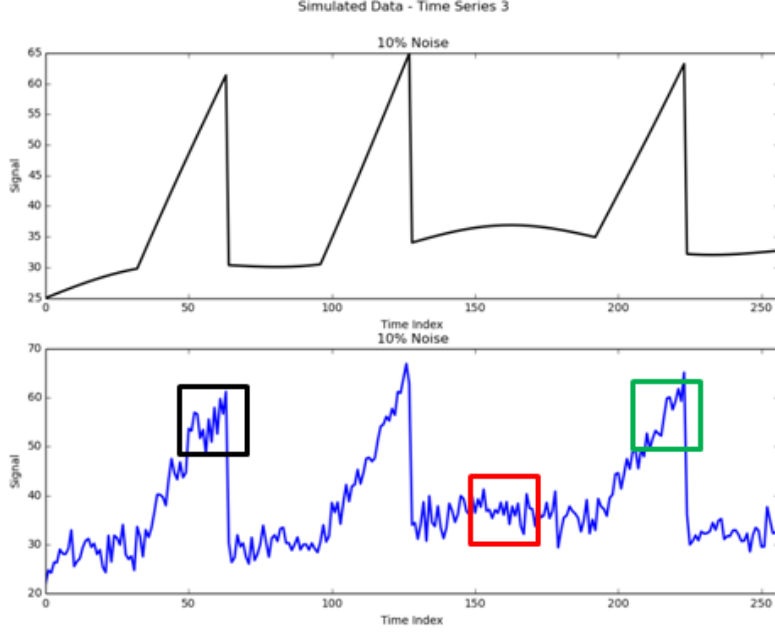


Figure 11: Non-local Means Window Comparison

Duval et al. [5] suggests that values of  $T$  near 20 or 30 work well for 2D images. This threshold does make sense for denoising time series. We will consider thresholds of the type  $T = \delta (\max Y_j - \min Y_j) |Y|$ , where  $\delta \in [0.0, 1.0]$ . This threshold is a percentage of an approximation of the maximum intensity interval distance. Duval et al. recommends window sizes of 5 or 7 for 2D image processing. As before, it is uncertain if these results translate to 1D time series denoising.

In this algorithm, the analyst can control the amount of smoothing via  $\beta$ , the preselection parameter  $\delta$ , the window size, and the portion of the time series that is compared. Figure 12 shows the performance of the non-local means algorithm with different values of  $\beta$ . Notice how similar the performance is to the bilateral filter, Figure 6.

As with the spatial filters, the  $\frac{|I|-1}{2}$  values on the edges do not have complete intervals, or windows. In order to calculate weights, we compare the incomplete neighborhood  $Y_i$  with incomplete neighborhoods around the other points  $Y_j$ . We adjust normalization factor  $z_i$  to ensure that the weight values in the incomplete interval still sum to 1.

With this edge treatment, it is simple to adjust the time series when a new data point is received. With the updated time series, the last  $\frac{|I|-1}{2}$  smoothed values can be updated and a new smoothed value can be calculated as before.

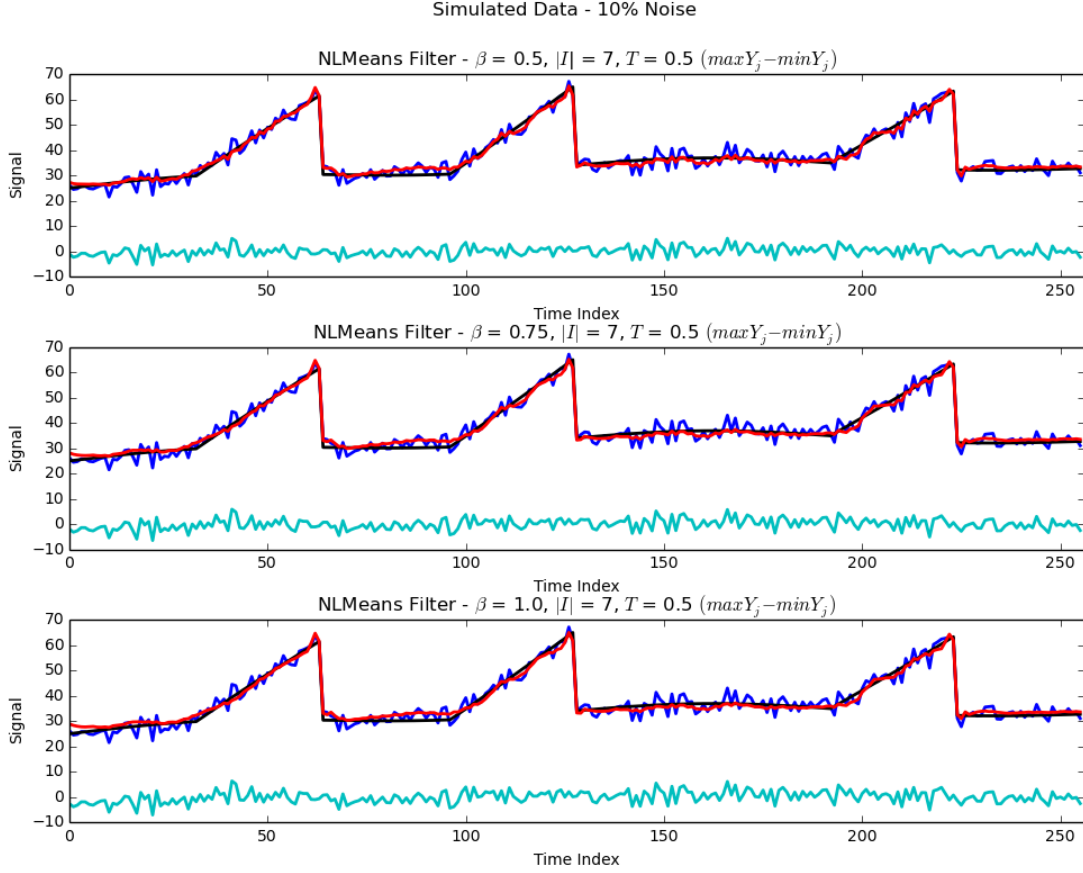


Figure 12: Non-Local Means with Simulated Data

## 2.4 Combination approaches

An obvious question to ask is the following: can we do better by combining denoising techniques, that is, applying them in succession to the data? A motivation for this is the non-local means algorithm, where we might expect to find better matches if the data was denoised first.

Iterating the box filter and Gaussian filter is well understood and is equivalent to using a box filter with a wider interval or Gaussian filter with a larger kernel,  $\sigma_d$ . We do not investigate these here. Iterating the Fourier transform or wavelet transform coefficient thresholding is equivalent to using a Fourier transform or wavelet transform filter with a higher frequency coefficient threshold. We do will not investigate these here either. We also do not consider combinations of frequency and spatial or statistical neighborhood techniques, as these have been investigated elsewhere.

Iterating a bilateral filter or non-local means filter is more complex. Also, the question of combining a bilateral filter and non-local means filter is open. We will investigate all three of these possibilities.



### 3 Design of experiments for empirical comparison

The denoising techniques described in Section 2 are evaluated using peak signal to noise ratio (PSNR), for known time series with added noise. PSNR [9] is the ratio between the maximum possible value of a time series and the maximum value of the noise. It is a measure of how noisy a signal is, and therefore how effective a denoising algorithm was and is calculated as follows:

$$PSNR = 10 \cdot \log_{10} \left( \frac{\left( \max_i \{y_i\} \right)^2}{MSE} \right)$$

where  $MSE$ , mean square error, is

$$MSE = \frac{1}{N} \sum_{i=0}^{N-1} (y_i - s_i)^2.$$

In real world data, we do not know the true time series values are in most cases, otherwise there is no need to denoise. Hence, PSNR can not be used to evaluate such data. Therefore, we create three synthetic time series that contain features similar to those in real world data. We select denoising parameters based on best PSNR values. Then, we view the effect of these parameters on real world data.

#### 3.1 Real world data

As an example of real world data, we consider the weather data from weather stations near the wind farms in the Bonneville Power Administration (BPA) balancing area. The data in the time series was sampled at 5 minute intervals. Each weather station measures seven variables, as shown in Figure 13, for the Augspurgen station on October 10, 2011.

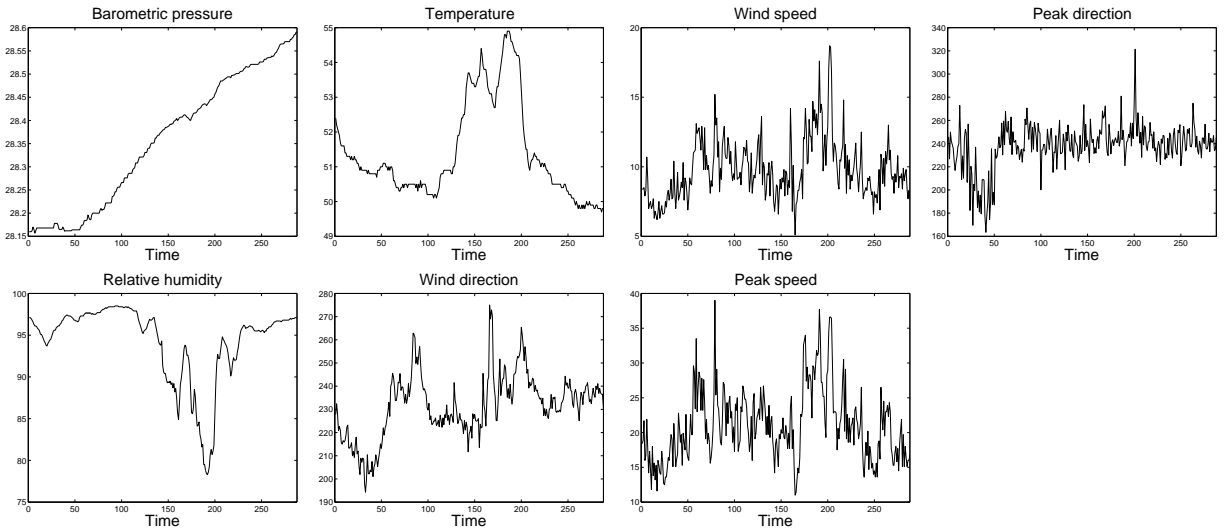


Figure 13: The Seven Weather Variables - Barometric Pressure, Temperature, Wind Speed, Peak Wind Speed, Wind Direction, Peak Wind Direction, and Relative Humidity - on October 10, 2011.

### 3.2 Synthetic data

One of the most popular noise models is Additive White Gaussian Noise (AWGN). AWGN is comprised of independent identically distributed real values from the Gaussian distribution with known, or more commonly unknown, standard deviation,  $\sigma_n$ .

Noise of a particular percentage is added by using  $\sigma_n = p \cdot v$  as the standard deviation of the distribution that generated the noise, where  $v = \max\{Y\} - \min\{Y\}$  is the maximum possible range of values that the time series  $Y$  could take and  $0 \leq p \leq 1$  is the percentage. To evaluate the performance we apply denoising techniques on three known time series with  $p = 1, 5, 10, 20$  and 30% AWGN noise added. Figure 14 displays the time series with  $p = 10\%$  noise added.

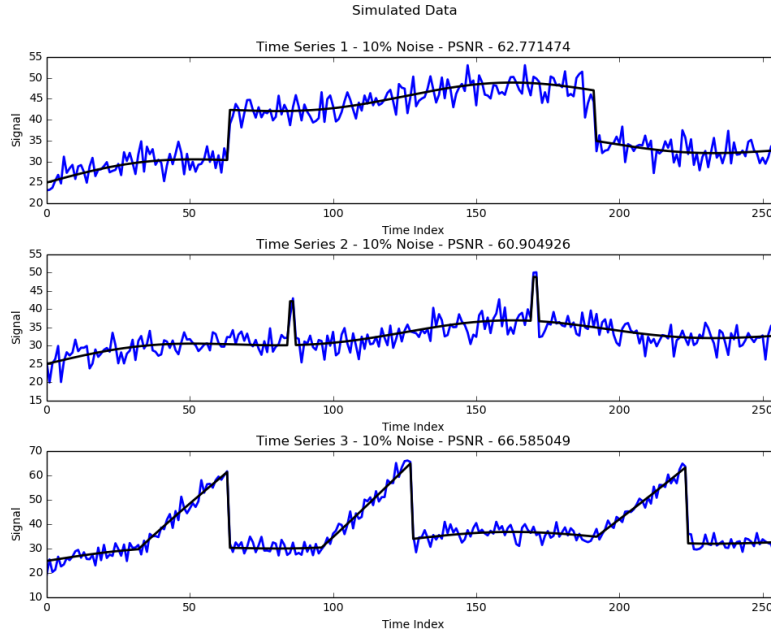


Figure 14: Known Time Series - 10% Noise

All of the time series were created by taking low frequency sinusoidal behavior and adding features of interest. There are a few interesting observations that can be made about the three time series.

The first time series was created by taking low frequency sinusoidal behavior and adding a sharp increase in intensity one quarter of the way through the time series and adding a sharp decrease in intensity three quarters of the way through the time series. In some cases the noise obscures the sharp increase or decrease in intensity, making it appear to be a more gradual increase or decrease in intensity. Noise can make features impossible to recover.

The second time series was created by taking low frequency sinusoidal behavior and adding two brief, sharp increases in intensity, at one and two thirds of the way through the time series. In some cases the noise can become indistinguishable from these features, making them impossible to recover.

The third time series was created by taking low frequency sinusoidal behavior and adding three sawtooth features, at one, three, and six eighths of the way through the time series. As with the first time series, it is possible for the noise to obscure the sharp decrease at the end of the saw tooth

	Time Series 1	Time Series 2	Time Series 3
1% Noise	85.546	72.155	67.335
5% Noise	81.121	70.323	66.857
10% Noise	73.582	66.015	65.038
20% Noise	63.132	57.815	60.987
30% Noise	56.497	51.587	56.220

Table 1: Noisy PSNR

features, making it appear to be a more gradual decrease in intensity.

The average PSNR values over 25 iterations of each the time series without denoising are shown in Table 1. An ideal result offers significantly higher PSNR values and is relatively insensitive to small changes in parameter choice.

### 3.3 Parameter settings

We evaluate the denoising techniques in a full factorial design over the following parameter ranges as shown in Table 2

All Methods	$p$ :	1%, 5%, 10%, 20% and 30%
Box Filter	$ I $ :	3, 5, 7 and 9
Gaussian Filter	$\sigma_d$ :	0.1, 1.0, 2.0, 3.0 and 4.0
Bilateral filter	$\sigma_d$ :	0.1, 1.0, 2.0, 3.0 and 4.0
	$\sigma_i$ :	$0.1\hat{\sigma}_n$ , $1.0\hat{\sigma}_n$ , $2.0\hat{\sigma}_n$ , $3.0\hat{\sigma}_n$ and $4.0\hat{\sigma}_n$
Frequency Methods	$\mu$ :	$0.1\sigma$ , $1.0\sigma$ , $2.0\sigma$ and $3.0\sigma$
	$\beta$ :	0.5, 0.75 and 1.0
Non-Local Means	$ Y $ :	3, 5, 7 and 9
	$\delta$ :	0.25, 0.5 and 0.75

Table 2: Parameter ranges.

We apply denoising methods using parameter settings described in Table 2 on the three synthetic time series data. For each parameter setting, we replicate the experiment five times to account for the variation in the noise. Each time, we create a new set of time series signals by adding different randomly generated noise using the same percentage  $p$ . After applying each methods on the synthetic data, PSNR values are summarized. Further iterations were run for finer resolution at parameter values that appeared to be near optimal for each denoising method, increasing the resolution of the grid in areas of interest.

## 4 Experimental results and parameter selection on synthetic data

The following are the experimental results from applying all parameter settings for the six denoising methods and combination approaches on the three synthetic time series data at different noise levels.

### 4.1 Box filter

Table 3 shows the best performance of the box filter in the search area. Table 4 shows the performance of the box filter when  $|I| = 7$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. The box filter consistently produces poor performance, but the performance is stable across the values of the parameter in the search area.

	Time Series 1	Time Series 2	Time Series 3
1% Noise	85.594	72.175	67.346
5% Noise	81.206	70.377	66.771
10% Noise	74.047	66.201	65.354
20% Noise	64.323	58.005	60.920
30% Noise	56.888	52.199	57.145

Table 3: Box Filter Best PSNR

	Time Series 1	Time Series 2	Time Series 3
1% Noise	85.549/99.9%	72.175/100.0%	67.346/100.0%
5% Noise	81.059/99.8%	70.181/99.7%	66.747/100.0%
10% Noise	73.249/98.9%	66.040/99.8%	64.923/99.3%
20% Noise	62.786/97.6%	57.932/99.9%	60.631/99.5%
30% Noise	56.165/98.7%	51.829/99.3%	56.082/98.1%

Table 4: Box Filter Selected Parameter PSNR -  $|I| = 7$

### 4.2 Gaussian filter

The Gaussian filter does not perform significantly better than the box filter.

Table 5 shows the best performance of the Gaussian filter in the search area. Table 6 shows the performance of the Gaussian filter when  $\sigma_d = 2.25$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. The Gaussian filter also consistently produces poor performance, but the performance is stable across the values of the parameter in the search area. The performance is slightly better than the box filter and slightly less stable.

	Time Series 1	Time Series 2	Time Series 3
1% Noise	83.257	71.659	74.807
5% Noise	80.684	70.459	79.871
10% Noise	75.844	68.646	69.177
20% Noise	69.529	60.971	62.031
30% Noise	61.243	56.495	58.172

Table 5: Gaussian Filter Best PSNR

	Time Series 1	Time Series 2	Time Series 3
1% Noise	83.257/100.0%	71.659/100.0%	63.953/85.5%
5% Noise	80.684/100.0%	70.459/100.0%	63.685/79.7%
10% Noise	75.844/100.0%	67.568/98.4%	62.980/91.0%
20% Noise	67.086/96.5%	60.005/98.4%	60.437/97.4%
30% Noise	59.973/97.9%	54.554/96.6%	56.797/97.6%

Table 6: Gaussian Filter Selected Parameter PSNR -  $\sigma_d = 2.25$

### 4.3 Bilateral filter

The bilateral filter offers significantly improved performance compared to both the box and Gaussian filters.

Table 7 shows the best performance of the bilateral filter in the search area. Table 8 shows the performance of the bilateral filter when  $\sigma_d = 2.5$  and  $\sigma_i = 2.5\hat{\sigma}_n$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. The bilateral filter performs well and is reasonably stable in the search area. The performance is significantly better than the box or Gaussian filters and slightly less stable.

	Time Series 1	Time Series 2	Time Series 3
1% Noise	127.251	128.396	121.790
5% Noise	97.303	96.758	96.698
10% Noise	81.774	78.128	84.987
20% Noise	69.794	63.453	70.033
30% Noise	62.657	59.049	61.736

Table 7: Bilateral Filter Best PSNR

1% Noise	124.947/98.2%	126.752/98.7%	110.432/90.7%
5% Noise	93.220/95.8%	92.841/96.0%	96.698/100.0%
10% Noise	79.580/97.3%	75.578/96.7%	84.480/99.4%
20% Noise	64.659/92.6%	60.585/95.5%	68.456/97.7%
30% Noise	57.875/92.4%	53.774/91.1%	60.891/98.6%

Table 8: Bilateral Filter Selected Parameters PSNR -  $\sigma_d = 2.5$ ,  $\sigma_i = 2.5\hat{\sigma}_n$

#### 4.4 Fourier transform

Fourier transform coefficient thresholding does not appear to be as effective as the bilateral filter, giving performance equivalent to the box and Gaussian filters.

Table 9 shows the best performance of Fourier transform coefficient thresholding in the search area. Table 10 shows the performance of Fourier transform coefficient thresholding when  $\mu = 0.15\sigma$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. Fourier transform coefficient thresholding particularly struggles with a fixed thresholding level, which is likely why methods such as SURE [12] are so popular with frequency based techniques. Fourier transform coefficient thresholding also has significantly less stable optimal parameters compared to the local neighborhood techniques.

	Time Series 1	Time Series 2	Time Series 3
1% Noise	75.495	64.912	72.728
5% Noise	74.657	65.029	71.950
10% Noise	69.444	61.559	66.948
20% Noise	63.094	57.928	58.394
30% Noise	59.586	57.348	51.886

Table 9: Fourier Transform Coefficient Thresholding Best PSNR

	Time Series 1	Time Series 2	Time Series 3
1% Noise	70.638/93.6%	62.517/96.3%	67.359/92.6%
5% Noise	70.752/94.8%	62.200/95.6%	66.589/92.5%
10% Noise	69.444/100.0%	61.559/100.0%	65.227/97.4%
20% Noise	53.774/85.2%	49.052/84.7%	55.580/95.2%
30% Noise	45.173/75.8%	41.630/72.6%	48.409/93.3%

Table 10: Fourier Transform Coefficient Thresholding Selected Parameter PSNR -  $\mu = 0.15\sigma$

## 4.5 Wavelet transform

Wavelet transform coefficient thresholding also gives performance similar to the box and Gaussian filters.

Table 11 shows the best performance of wavelet transform coefficient thresholding in the search area. Table 12 shows the performance of wavelet transform coefficient thresholding when  $\mu = 0.3\sigma$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. Wavelet transform coefficient thresholding also struggles with a fixed thresholding level and also struggles high levels of noise. At low levels of noise wavelet transformation coefficient thresholding is almost as effective as the bilateral filter. Wavelet transform coefficient thresholding also has significantly less stable optimal parameters compared to the local neighborhood techniques.

	Time Series 1	Time Series 2	Time Series 3
1% Noise	104.704	105.849	103.423
5% Noise	76.321	74.722	80.334
10% Noise	64.351	61.333	67.268
20% Noise	51.839	49.754	54.477
30% Noise	46.453	51.175	47.660

Table 11: Wavelet Transform Coefficient Thresholding Best PSNR

	Time Series 1	Time Series 2	Time Series 3
1% Noise	87.042/83.1%	86.556/81.8%	91.880/88.8%
5% Noise	76.321/100.0%	73.853/98.8%	79.821/99.4%
10% Noise	63.265/98.3%	61.333/100.0%	67.268/100.0%
20% Noise	50.248/96.9%	46.852/94.2%	52.868/97.0%
30% Noise	44.178/95.1%	40.057/78.3%	47.362/99.4%

Table 12: Wavelet Transform Coefficient Thresholding Selected Parameter PSNR -  $\mu = 0.3\sigma$

## 4.6 Non-local means

Non-local means offers performance that is nearly equivalent to the bilateral filter.

Table 13 shows the best performance of the bilateral filter in the search area. Table 14 shows the performance of the bilateral filter when  $\beta = 0.5$ ,  $|I| = 7$ , and  $T = 0.75 (\max Y_j - \min Y_j)$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. The non-local means algorithm has similar, but slightly inferior performance to the bilateral filter.

It is worth noting that the optimal value for the parameter  $\beta$  did increase as the noise level of the time series increased. It is an open question if  $\beta$  could be set with a fixed relationship between the variance of the time series and the estimated noise variance.

Theoretically, non-local means should work better on longer time series. An area of future research would be to consider this stability analysis on significantly longer time series. It is known that the computation time is much longer and the preselection is much more significant for non-local means on large time series.

	Time Series 1	Time Series 2	Time Series 3
1% Noise	114.852	112.238	101.050
5% Noise	89.317	89.332	92.007
10% Noise	77.760	75.828	79.996
20% Noise	65.997	60.698	68.439
30% Noise	58.928	54.630	62.217

Table 13: Non-Local Means Filter Best PSNR

	Time Series 1	Time Series 2	Time Series 3
1% Noise	114.852/98.0%	112.238/98.1%	101.050/98.0%
5% Noise	89.317/98.6%	89.332/97.4%	92.007/98.1%
10% Noise	77.760/95.7%	75.828/95.1%	79.996/98.8%
20% Noise	65.997/95.5%	60.698/95.0%	68.439/96.6%
30% Noise	58.928/96.5%	54.630/99.6%	62.217/96.1%

Table 14: Non-Local Means Filter Selected Parameters PSNR -  $\beta = 0.5$ ,  $|I| = 7$ ,  $\delta = 0.75$

#### 4.7 Performance of combination approaches

We consider several combination techniques: two different iterations of the bilateral filter, two iterations of the same bilateral filter, iterating the bilateral filter until the result changes by less than 1%, two different iterations of non-local means, and a combination of the bilateral filter and non-local means.

- **Two different bilateral filters** Two different iterations of the bilateral filter offered slightly improved performance compared to a single iteration of the bilateral filter.

Table 15 shows the best performance of two different iterations of the bilateral filter in the search area. Table 16 shows the performance of two different iterations of the bilateral filter when  $\sigma_{d1} = 2.5$ ,  $\sigma_{i1} = 2.0\hat{\sigma}_n$ ,  $\sigma_{d2} = 3.0$ , and  $\sigma_{i2} = 2.5\hat{\sigma}_n$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. Two different iterations of the bilateral filter performs well and is reasonably stable in the search area. The performance is slightly better than a single iteration of the bilateral filter and also slightly less stable.

- **Two same bilateral filters**



	Time Series 1	Time Series 2	Time Series 3
1% Noise	128.702	129.586	106.938
5% Noise	102.541	101.245	97.853
10% Noise	87.505	84.902	88.481
20% Noise	72.558	67.433	74.769
30% Noise	65.472	60.479	65.889

Table 15: 2 Different Bilateral Filters Best PSNR

	Time Series 1	Time Series 2	Time Series 3
1% Noise	124.219/96.5%	124.732/96.3%	98.953/92.5%
5% Noise	97.096/94.7%	97.972/96.8%	92.550/94.6%
10% Noise	83.758/95.7%	78.568/92.5%	84.086/95.0%
20% Noise	68.950/95.0%	62.641/92.9%	72.100/96.4%
30% Noise	62.052/94.8%	58.350/96.5%	65.094/98.8%

Table 16: 2 Different Bilateral Filters Selected Parameters PSNR -  
 $\sigma_{d1} = 2.5$ ,  $\sigma_{i1} = 2.0\hat{\sigma}_n$ ,  $\sigma_{d2} = 3.0$ ,  $\sigma_{i2} = 2.5\hat{\sigma}_n$

Two iterations of the same bilateral filter offered slightly improved performance compared to a single iteration of the bilateral filter.

Table 17 shows the best performance of two iterations of the same Bilateral filter in the search area. Table 18 shows the performance of two iterations of the same bilateral filter when  $\sigma_{d1} = 2.5$ ,  $\sigma_{i1} = 2.0\hat{\sigma}_n$ ,  $\sigma_{d2} = 3.0$ , and  $\sigma_{i2} = 2.5\hat{\sigma}_n$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. Two iterations of the same bilateral filter performs well and is reasonably stable in the search area. The performance is comparable to two different iteration of the bilateral filter.

	Time Series 1	Time Series 2	Time Series 3
1% Noise	126.790	128.683	108.250
5% Noise	103.260	101.220	99.692
10% Noise	87.270	84.463	88.091
20% Noise	71.926	66.703	73.766
30% Noise	65.420	57.585	64.878

Table 17: 2 Same Bilateral Filters Best PSNR

- **Bilateral filter iterated to tolerance**

Multiple iterations of the same bilateral filter offered performance comparable to a single

	Time Series 1	Time Series 2	Time Series 3
1% Noise	124.104/97.9%	125.701/97.7%	97.981/90.5%
5% Noise	98.423/95.3%	98.219/97.0%	91.889/92.2%
10% Noise	83.413/95.6%	80.776/95.6%	84.786/96.2%
20% Noise	69.228/96.2%	65.098/97.6%	71.679/97.2%
30% Noise	61.121/93.4%	57.585/100.0%	64.878/100.0%

Table 18: 2 Same Bilateral Filters Selected Parameters PSNR -  $\sigma_d = 3.0$ ,  $\sigma_i = 2.0\hat{\sigma}_n$

iteration of the bilateral filter.

Table 19 shows the best performance of multiple iterations of the same Bilateral filter in the search area. Table 20 shows the performance of multiple iterations of the same bilateral filter when  $\sigma_d = 3.0$ , and  $\sigma_i = 2.5\hat{\sigma}_n$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. Multiple iterations of the same bilateral filter performs well and is reasonably stable in the search area. The performance can be lower than a single iteration of the bilateral filter. The stability of the optimal parameters is lower than for a single iteration of the bilateral filter.

	Time Series 1	Time Series 2	Time Series 3
1% Noise	126.387	128.682	120.867
5% Noise	100.102	102.022	98.848
10% Noise	86.418	85.543	87.412
20% Noise	72.479	67.397	73.564
30% Noise	63.684	60.820	65.202

Table 19: Iterated Bilateral Filter Best PSNR

	Time Series 1	Time Series 2	Time Series 3
1% Noise	123.012/97.3%	126.306/98.2%	96.433/79.8%
5% Noise	99.427/99.3%	97.578/95.6%	93.087/94.2%
10% Noise	84.112/97.3%	74.561/87.2%	84.502/96.7%
20% Noise	69.483/95.9%	64.130/95.2%	73.112/99.4%
30% Noise	62.807/98.6%	53.906/88.6%	63.868/98.0%

Table 20: Iterated Bilateral Filter Selected Parameters PSNR -  $\sigma_d = 3.0$ ,  $\sigma_i = 2.5\hat{\sigma}_n$

- **Two different non-local means filters**

Two iterations of non-local means offered slightly worse performance compared to a single

iteration of non-local means.

Table 21 shows the best performance of two iterations of non-local means in the search area. Table 22 shows the performance of two iterations of non-local means when  $\beta_1 = 0.3333$ ,  $|Y|_1 = 7$ ,  $\delta_1 = 0.6666$ ,  $\beta_2 = 0.3333$ ,  $|Y|_2 = 7$ , and  $\delta_2 = 0.3333$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. Two iterations of non-local means does not perform as well as a single iteration but is reasonably stable in the search area.

	Time Series 1	Time Series 2	Time Series 3
1% Noise	107.847	104.524	91.865
5% Noise	89.297	90.918	89.758
10% Noise	77.988	76.564	81.663
20% Noise	67.315	64.974	69.230
30% Noise	60.147	59.249	62.978

Table 21: 2 Different Non-Local Means Best PSNR

	Time Series 1	Time Series 2	Time Series 3
1% Noise	107.847/100.0%	102.152/97.7%	90.914/99.0%
5% Noise	87.114/97.6%	87.728/96.5%	86.901/96.8%
10% Noise	76.152/97.6%	75.499/98.6%	80.257/98.3%
20% Noise	62.439/92.8%	60.393/92.9%	66.626/96.2%
30% Noise	59.260/98.5%	55.082/93.0%	60.762/96.5%

Table 22: 2 Different Non-Local Means Selected Parameters PSNR -  $\beta_1 = 0.3333$ ,  $|Y|_1 = 7$ ,  $\delta_1 = 0.6666$ ,  $\beta_2 = 0.3333$ ,  $|Y|_2 = 7$ ,  $\delta_2 = 0.3333$

- **Bilateral and non-local means combination**

The combination of the bilateral filter and non-local means offered improved performance compared to either method alone.

Table 23 shows the best performance of the combination of the bilateral filter and non-local means in the search area. Table 24 shows the performance of the combination of the bilateral filter and non-local means when  $\sigma_d = 2.5$ ,  $\sigma_i = 1.8\hat{\sigma}_n$ ,  $\beta = 0.5$ ,  $|Y| = 7$ , and  $\delta = 0.9$ . The PSNR value for this parameter setting and the percentage of the maximum PSNR value are listed in each cell. The combination of the bilateral filter and non-local means performs well and is reasonably stable in the search area.

#### 4.8 Comparison using 10% noise added data

Figure 25 shows a comparison of the best performance of each method for all three time series at 10% noise, and Figure 26 shows a comparison of the selected parameter performance between all

	Time Series 1	Time Series 2	Time Series 3
1% Noise	116.272	114.415	110.231
5% Noise	100.498	97.932	97.620
10% Noise	87.153	82.641	86.879
20% Noise	73.244	66.868	75.505
30% Noise	67.219	60.023	84.472

Table 23: Bilateral and Non-Local Means Filters Best PSNR

	Time Series 1	Time Series 2	Time Series 3
1% Noise	114.572/98.5%	111.731/97.7%	94.137/85.4%
5% Noise	94.730/94.3%	94.948/97.0%	89.549/91.7%
10% Noise	79.659/91.4%	78.388/94.9%	77.953/89.7%
20% Noise	66.427/90.7%	61.955/92.7%	66.799/88.5%
30% Noise	60.274/89.7%	57.825/96.3%	84.472/100.0%

Table 24: Bilateral and Non-Local Means Filters Selected Parameters PSNR -  
 $\sigma_d = 2.5$ ,  $\sigma_i = 1.8\hat{\sigma}_n$ ,  $\beta = 0.5$ ,  $|Y| = 7$ ,  $\delta = 0.9$

methods considered for all three time series at 10% noise.

Some trends can be seen from these charts. The box filter, Gaussian filter, Fourier transform coefficient thresholding, and wavelet transform coefficient thresholding consistently offer the worst performance, and all of these methods may in fact reduce PSNR for the time series. Of the remaining techniques, multiple iterations of the bilateral filter to tolerance has very inconsistent performance, sometime performing well and other times being the worst of the remaining techniques.

Two iterations of non-local means often has worse performance than a single iteration, and two different iterations of the bilateral filter also often has worse performance than a single iteration. The consistent top performers are the bilateral filter and two iterations of the same bilateral filter. These techniques offered a 15% to 30% improvement with the selected parameters.

Figures 15, 16, and 17 show the performance of the methods without the combinations on the known time series with 10% noise added.

The spike at time index 85 in time series 2 is a good example of a feature that is sufficiently obscured by noise to make it almost impossible to fully recover. The increase in intensity at time index 64 in time series 1 provides an example of the intensity of the jump being decreased due to positive noise values on the lower side of the jump and negative noise values on the upper side of the jump.

As expected, the box and Gaussian filters destroy features in these time series while the bilateral filter or non-local means appear to do well at denoising the time series while retaining features. This can be seen particularly well with the jumps in time series 1, the spikes in time series 2, and the sawteeth in time series 3.

Fourier transform and wavelet transform coefficient thresholding appear to denoise less than

	Time Series 1	Time Series 2	Time Series 3
Noisy	73.582	66.015	65.038
Box Filter	74.047	66.201	65.354
Gaussian Filter	75.844	68.646	69.177
Bilateral Filter	81.774	78.128	84.987
Fourier Transform	69.444	61.559	66.948
Wavelet Transform	64.351	61.333	67.268
Non-Local Means	77.760	75.828	79.996
2 Different Bilateral	87.505	84.902	88.481
2 Same Bilateral	87.270	84.463	88.091
Iterated Bilateral	86.418	85.543	87.412
2 Different NL Means	77.988	76.564	81.663
Bilateral NL Means	87.153	82.641	86.879

Table 25: Performance Comparison at 10% Noise - Best Performance

either the bilateral filter or non-local means in all three time series.

## 5 Experimental results on real world data

Figures 18, 19, and 20 show real data that is similar to the three known time series that were investigated above.

As expected, the box and Gaussian filters destroy features in these time series while the bilateral filter or non-local means appear to do well at denoising the time series while retaining features. This can be seen particularly well at time indices 110 and 480 for time series 1 and at time index 580 for time series 2.

Fourier transform and wavelet transform coefficient thresholding appear to do better than expected but denoise less than the bilateral filter or non-local means for time series 1 and 2.

## 6 Conclusions

The box filter, Gaussian filter, Fourier transform coefficient thresholding, and wavelet transform coefficient thresholding consistently offer the worst performance, and all of these methods may in fact reduce PSNR for the time series. Also, Fourier transform coefficient thresholding is difficult to implement well for incremental time series. These techniques are not recommended as implemented. The wavelet transform can be improved with better choice of the family of wavelets.

Frequency based techniques such as Fourier transform coefficient thresholding or wavelet transform coefficient thresholding seem to do particularly poorly with a fixed parameter value. The more common practice with frequency techniques is to use SURE or another metric to fine tune the denoising parameters.

	Time Series 1	Time Series 2	Time Series 3
Noisy	73.582	66.015	65.038
Box Filter	73.249/98.9%	66.040/99.8%	64.923/99.3%
Gaussian Filter	75.844/100.0%	67.568/98.4%	62.980/91.0%
Bilateral Filter	79.580/97.3%	75.578/96.7%	84.480/99.4%
Fourier Transform	69.444/100.0%	61.559/100.0%	65.227/97.4%
Wavelet Transform	63.265/98.3%	61.333/100.0%	67.268/100.0%
Non-Local Means	77.760/95.7%	75.828/95.1%	79.996/98.8%
2 Different Bilateral	83.758/95.7%	78.568/92.5%	84.086/95.0%
2 Same Bilateral	83.413/95.6%	80.776/95.6%	84.786/96.2%
Iterated Bilateral	84.112/97.3%	74.561/87.2%	84.502/96.7%
2 Different NL Means	76.152/97.6%	75.499/98.6%	80.257/98.3%
Bilateral NL Means	79.659/91.4%	78.388/94.9%	77.953/89.7%

Table 26: Performance Comparison at 10% Noise - Selected Parameters

Non-local means offers a consistent improvement in PSNR, but its performance can be improved by paring it with a bilateral filter. The parameter  $\beta$  has an important impact on the performance of non-local means. A future area of research should be to determine if some relationship between the variance of the time series and the estimated noise variance could be used to chose  $\beta$ . Also, non-local means should theoretically perform better with longer time series, where more matching neighborhoods are possible. This possibility should be investigated. It is important to keep in mind that there is a tradeoff between keeping the data set small to ensure reasonable computation time and providing sufficient data to ensure good performance for non-local means.

One or two iterations of the same bilateral filter appears to offer the best consistent performance. Both have relatively stable optimal parameter settings, with a single iteration of the bilateral filter being slightly more stable. Other versions of multiple iterations of a bilateral filter offer less consistent results.

Note that only Gaussian white noise was considered in this paper. In future work, non-Gaussian noise will be considered in the experiments for parameter settings. Instead of the design of experiments used in this paper, possible methods that could automatically find thresholds or parameters for denoising methods will also be explored.

## Acknowledgment

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Simulated Data - 10% Noise - Time Series 1

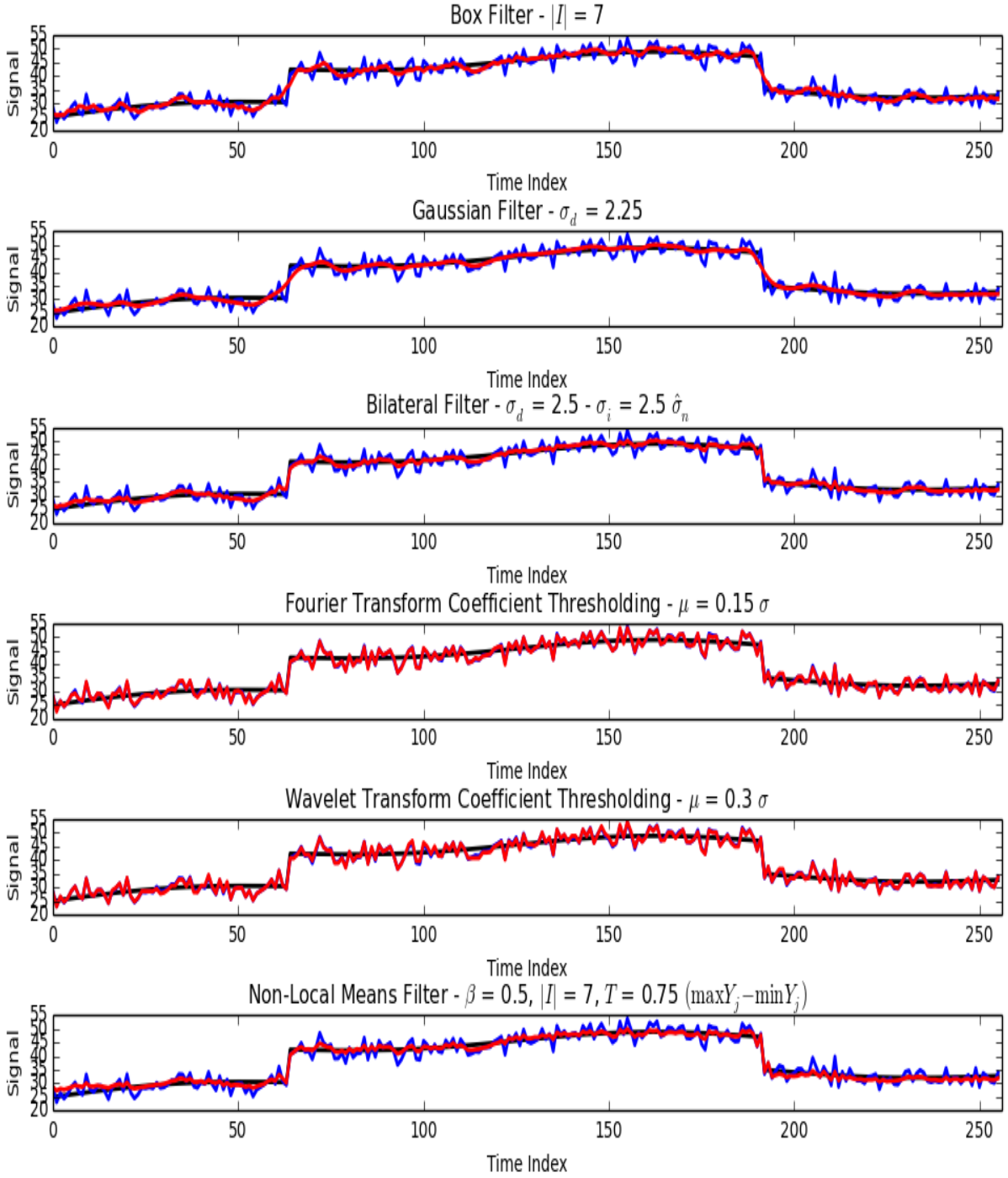


Figure 15: Comparison on Simulated Data - Time Series 1

Simulated Data - 10% Noise - Time Series 2

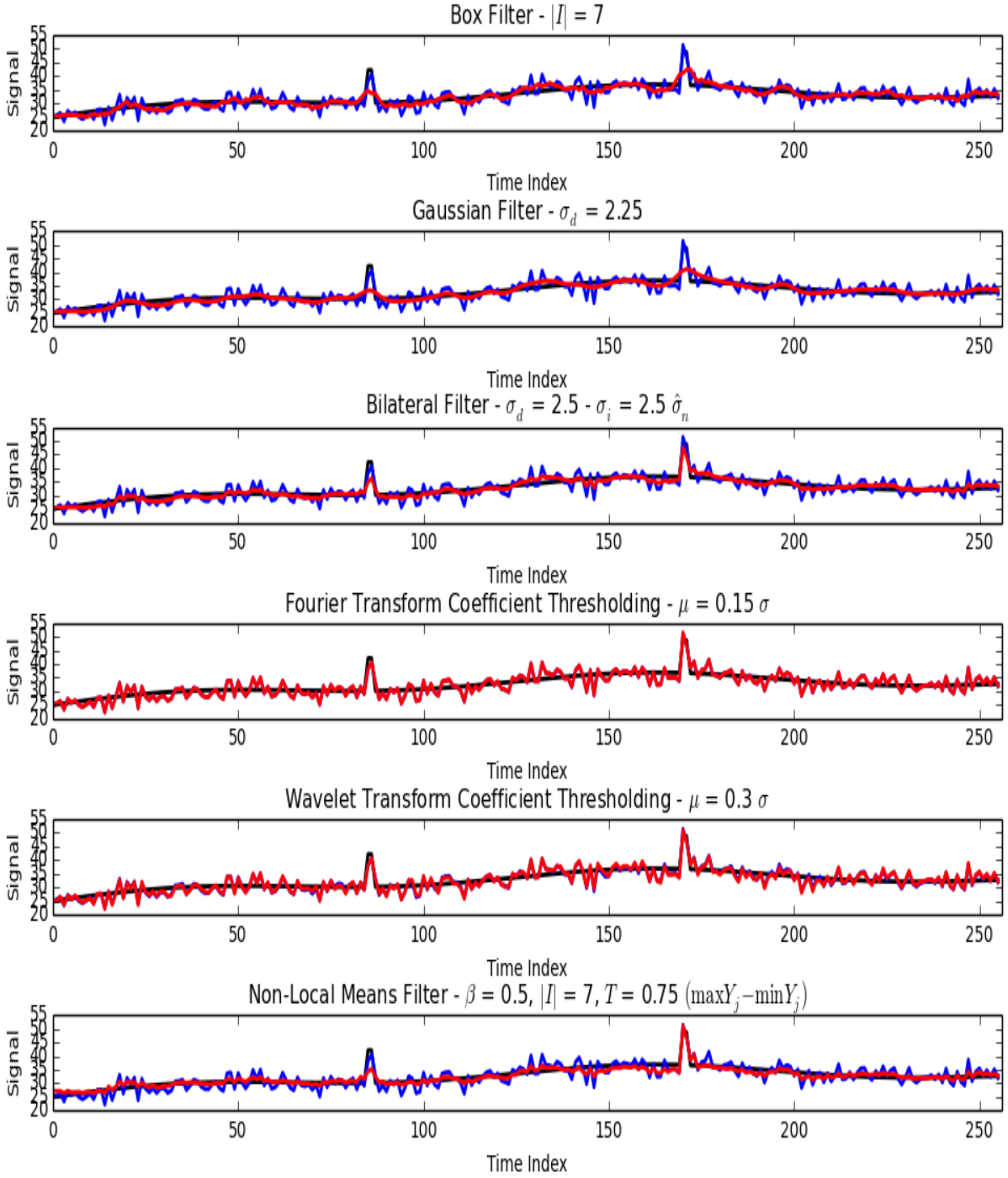


Figure 16: Comparison on Simulated Data - Time Series 2



Simulated Data - 10% Noise - Time Series 3

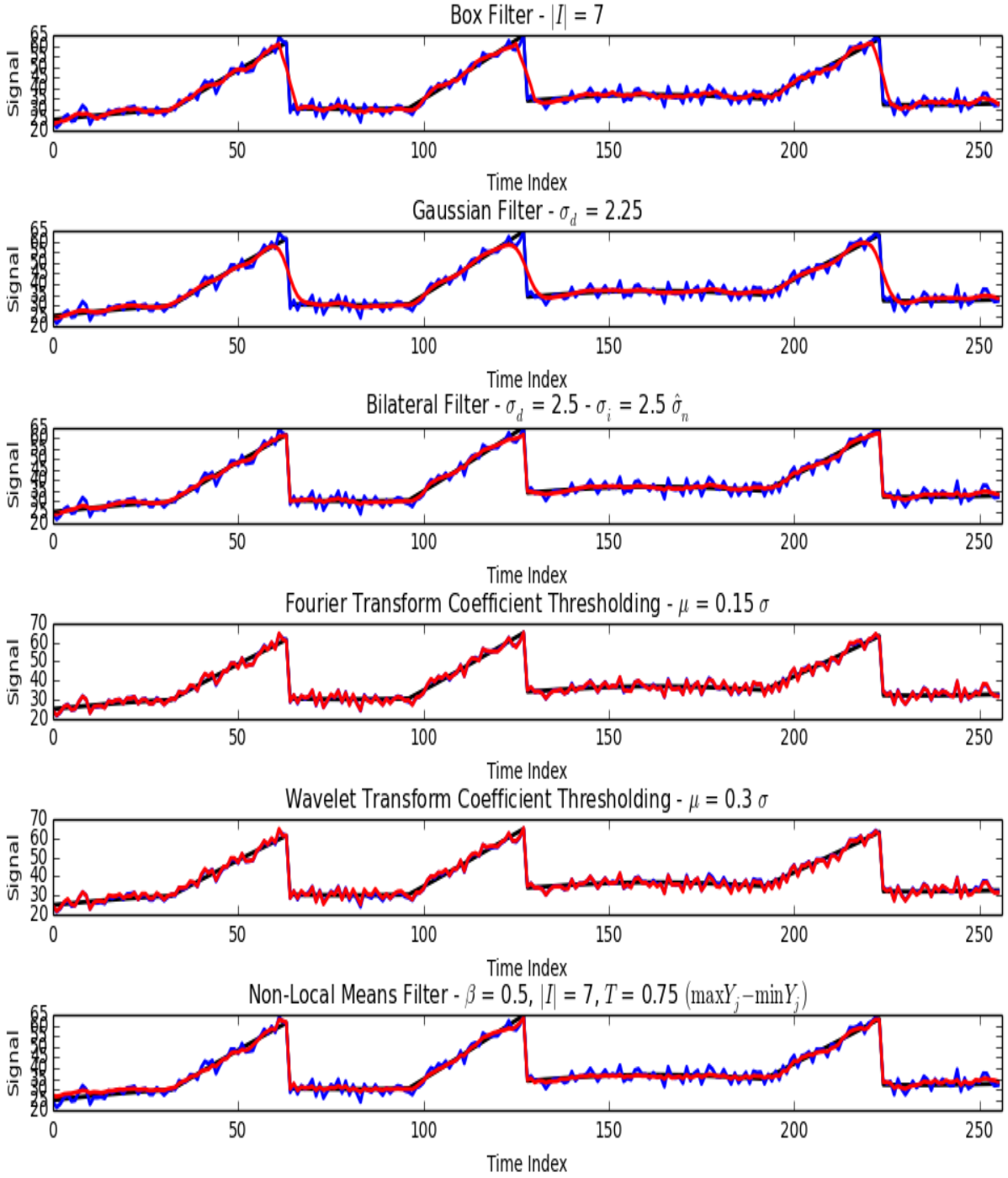


Figure 17: Comparison on Simulated Data - Time Series 3

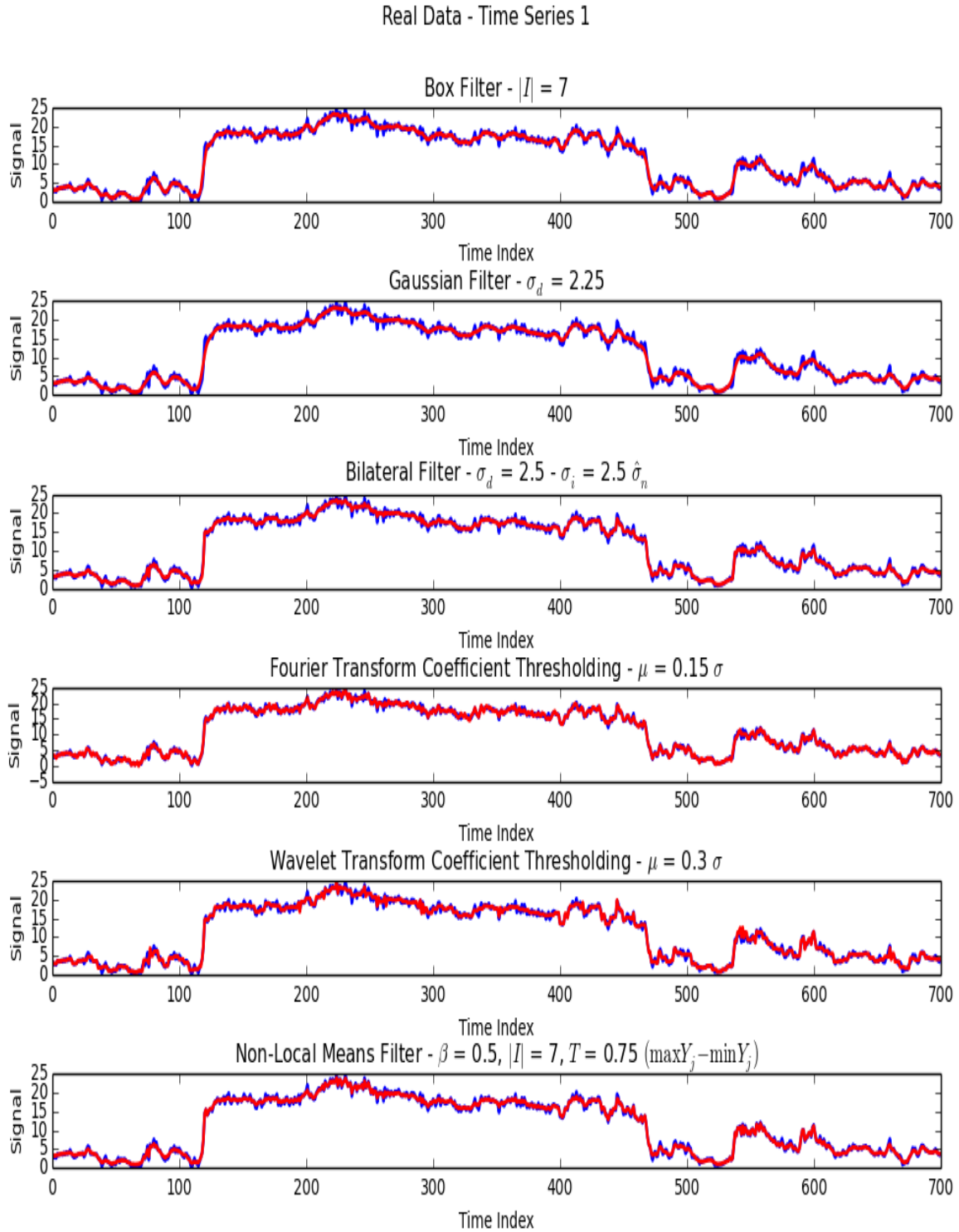


Figure 18: Comparison on Real Data - Time Series 1

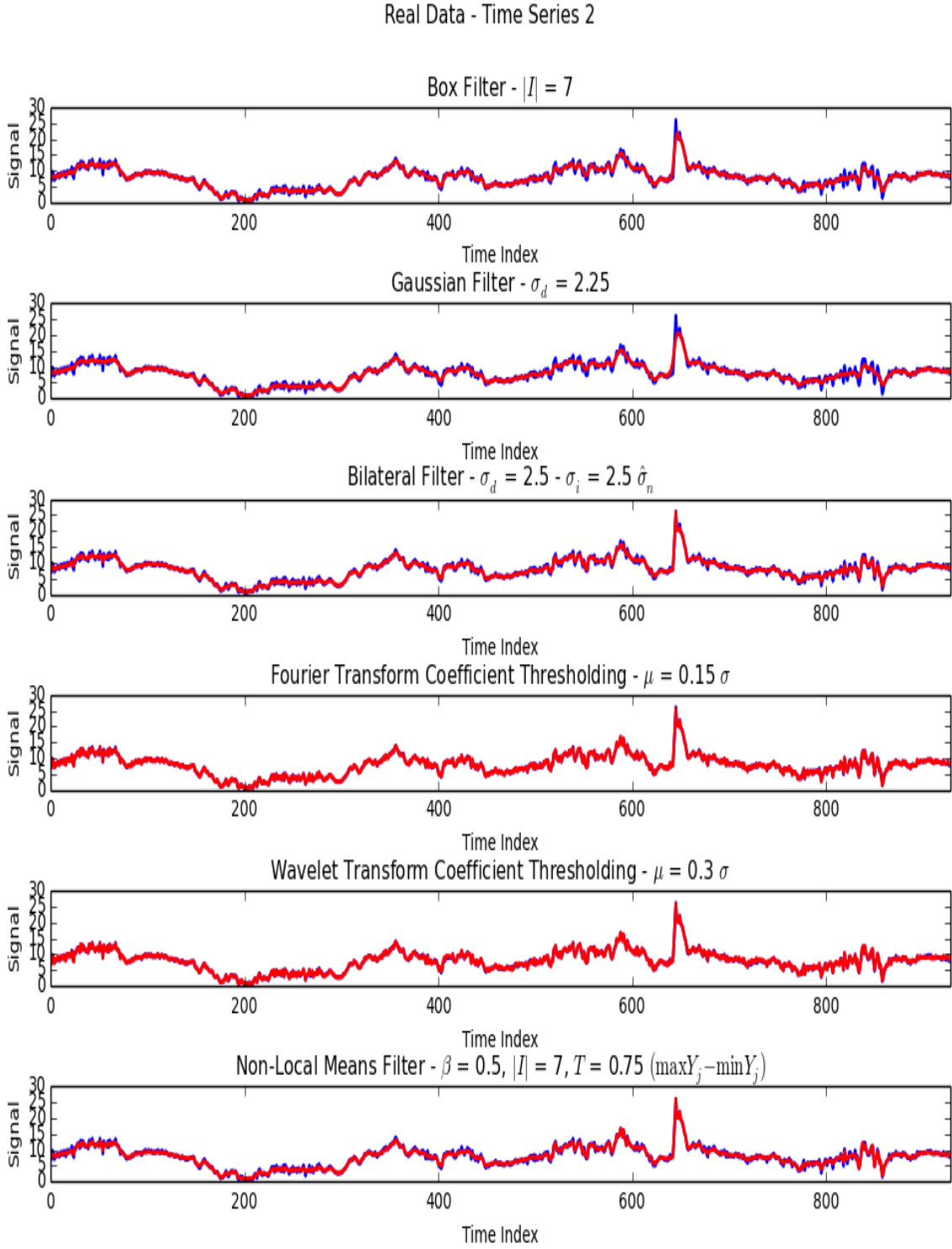


Figure 19: Comparison on Real Data - Time Series 2

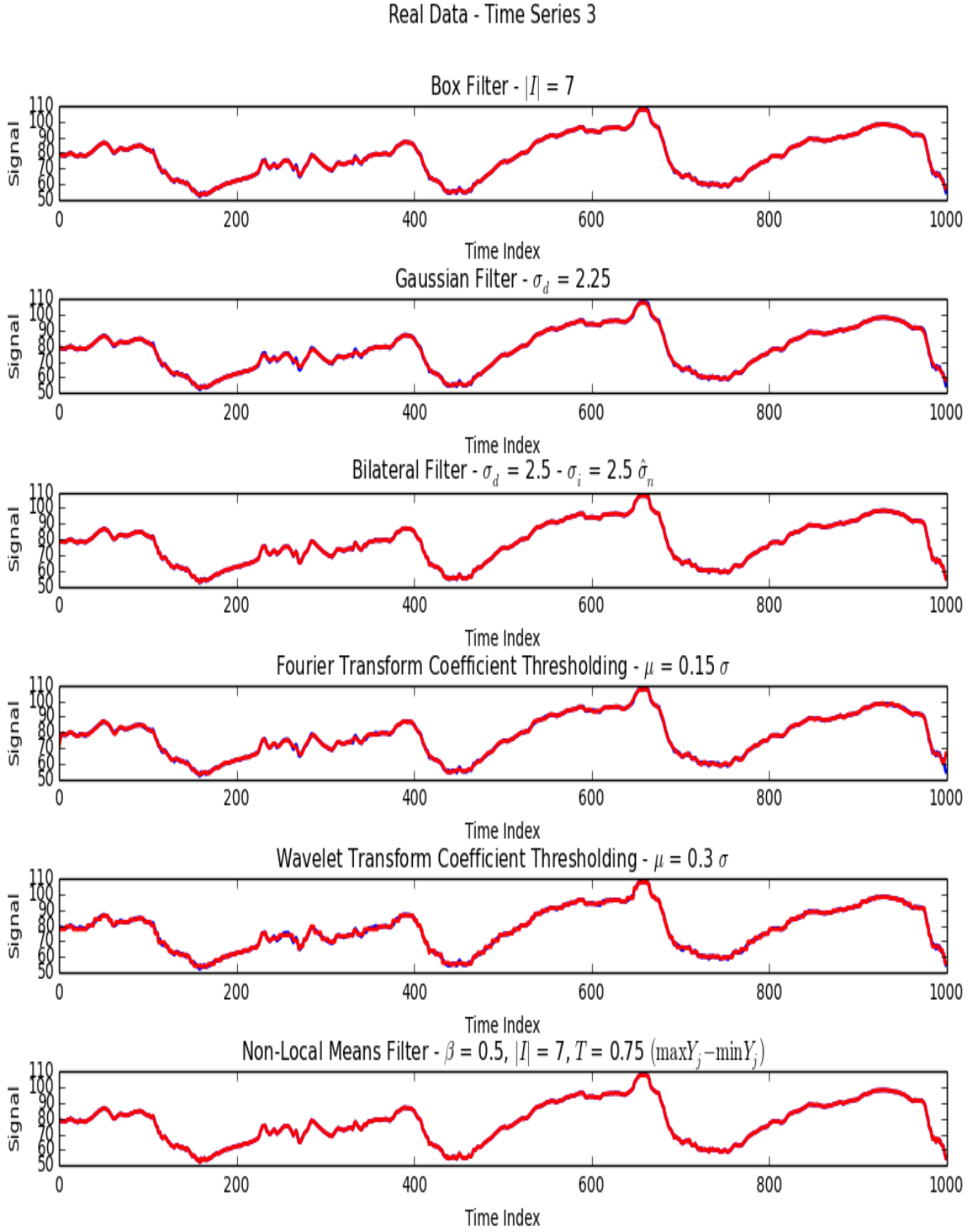


Figure 20: Comparison on Real Data - Time Series 3

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